

Article

Predicting and Mapping Dominant Height of Oriental Beech Stands Using Environmental Variables in Sinop, Northern Turkey

Ismet Yener ^{1,*}  and Engin Guvendi ²

¹ Department of Forest Engineering, Faculty of Forestry, Artvin Coruh University, Artvin 08100, Turkey

² Department of Forestry, Kürtün Vocational School, Gümüşhane University, Gümüşhane 29810, Turkey; eguvendi28@gumushane.edu.tr

* Correspondence: yener@artvin.edu.tr

Abstract: The dominant height of forest stands (SDH) is an essential indicator of site productivity in operational forest management. It refers to the capacity of a particular site to support stand growth. Sites with taller dominant trees are typically more productive and may be more suitable for certain management practices. The present study investigated the relationship between the dominant height of oriental beech stands and numerous environmental variables, including physiographic, climatic, and edaphic attributes. We developed models and generated maps of SDH using multilinear regression (MLR) and regression tree (RT) techniques based on environmental variables. With this aim, the total height, diameter at breast height, and age of sample trees were measured on 222 sample plots. Additionally, topsoil samples (0–20 cm) were collected from each plot to analyze the physical and chemical soil properties. The statistical results showed that latitude, elevation, mean annual maximum temperature, and several soil attributes (i.e., bulk density, field capacity, organic carbon, and pH) were significantly correlated with the SDH. The RT model outperformed the MLR model, explaining 57% of the variation in the SDH with an RMSE of 2.37 m. The maps generated by both models clearly indicated an increasing trend in the SDH from north to south, suggesting that elevation above sea level is a driving factor shaping forest canopy height. The assessments, models, and maps provided by this study can be used by forest planners and land managers, as there is no reliable data on site productivity in the studied region.

Keywords: stand productivity; site factors; multiple linear regression; regression tree; modeling



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1. Introduction

Site quality is a combination of climatic, physiographic, edaphic, and biotic factors affecting the potential of trees to produce aboveground biomass in the forest. A common indicator of site productivity in forestry is the site index (SI), referring to the stand dominant height (SDH) at a standard age (e.g., 50 or 100 years) [1]. The calculation of the SI is based on the SDH and age measurements of 100 trees per hectare (also known as h100) [1,2]. The SI is an essential parameter in ecology and forest management when deciding on afforestation and reforestation locations [3]. Measuring the SDH and tree ages on the ground is challenging because of time, labor, and cost restrictions [4,5]. Therefore, many researchers seek to predict or model site productivity cost-effectively. The initial studies on modeling forest site productivity used only parametric techniques, e.g., multilinear regression (MLR). Recently, some studies have also used non-parametric techniques, such as fuzzy logic, an artificial neural network (ANN), the general additive model (GAM), and the classification and regression tree (CART), which are more accurate and precise than the former ones to estimate the growth and height of dominant trees [6–8]. Among the previously mentioned techniques, CART is a non-parametric technique used to model site productivity [9,10]. Recently, studies using the CART technique have increased worldwide [4,7,11–16].

Many ecological variables, including climatic, topographic, and edaphic variables, have been used in site productivity modeling studies because of their vital effects on plant growth. Of these factors, the climate plays a crucial role in characterizing global forests' distribution, carbon storage, and development and is also directly related to biomass production. For example, temperature governs photosynthesis and carbon loss, and precipitation is responsible for available water, affecting the nutrient uptake, leaf area index, and overall stand productivity. Therefore, moving any plant species away from the optimum climatic conditions may create negativities in development [17,18]. The topographic variables, especially elevation along with slope and aspect, which control the spatial and temporal distribution of climatic parameters such as temperature, precipitation, and solar radiation, have a prominent influence on stand productivity and species composition [19]. The last ecological factor used in such studies is soil, whose physical and chemical properties (texture, bulk density, available water capacity, organic carbon, electrical conductivity, and pH) have an essential effect on plant productivity via either root growth and nutrient uptake or directly or indirectly altering soil aeration and respiration. Soils may also affect the tree species that can be established in a particular area, resulting in functional traits found there [20].

Recently, modeling studies have used ecological variables extracted from freely available spatial datasets, e.g., satellite images, which make modeling efforts more time, labor, and cost efficient. The normalized difference vegetation index (NDVI) is one of the most used variables obtained from images and correlated with site productivity and biomass besides others, such as the normalized difference water index (NDWI), vegetation difference index (VDI), and topographic wetness index (TWI) [5,21–23].

While topographic variables (e.g., latitude–longitude, elevation, slope, aspect, and distance to the sea) can be extracted from maps generated using a digital elevation model (DEM) [24], climatic (e.g., temperature and precipitation) and edaphic variables (e.g., organic carbon, clay content, and bulk density) are available from some digital platforms, such as worldclim.org [25] and OpenLandMap.org [26–28]. Recently, some other databases or platforms, such as Google Earth Engine (GEE) and Microsoft's Planetary Computer (MPC), which encourage users to analyze, manipulate, and download spatial data, have been used by some researchers [29].

Oriental beech (*Fagus orientalis* Lipsky) is a commercial tree species in Turkey. Its growth and productivity need to be determined practically in a timely manner. This species natively spreads from the Balkans and Turkish Thrace to the Caucasus and Crimea, crossing the Strandja Mountains, Istanbul, and Kocaeli Peninsula. It also has a narrow distribution area in northern Aegean [30]. This species has a distribution area of 1,878,049 ha, covering around 8% of Turkey's forestlands, and ranks fourth among all native species in terms of area coverage [31].

The present study aimed to model and map the SDH of oriental beech stands by regression tree (RT) and multilinear regression techniques using readily available environmental variables. It is believed that the results of this study are vital in decision-making processes in forest management and land planning.

2. Materials and Methods

2.1. Site Description

The research area is within the border of Ayancık, Sinop, and Turkeli Forest Enterprises, affiliated with the Sinop Regional Directorate of Forestry. The study area is situated between 41°40'50"–42°05'53" N latitudes and 34°13'28"–35°12'40" E longitudes (Figure 1). There is a sharp increase in elevation in the study area, except for the narrow coastal plains in Ayancık. The minimum altitude starts from sea level and reaches 1500–1800 m in the Eastern part of the Mountains İsfendiyyar along Sinop Province [32].

The area's geological structure mainly comprises Upper Cretaceous, Eocene, and Neogene-aged sedimentary rocks and Quarternary-aged marine deposits [33]. There are mostly four great soil groups in the study area according to the USDA soil taxonomy:

hapludults, dystrudepts, hapludalfs, and udivitrands affiliated to the order of ultisols, inceptisols, alfisols, and mollisols, respectively [34]. The climate in Sinop is a typical Black Sea regime: while the mean annual total precipitation ranges from 675 mm to 1012 mm, the mean annual temperature changes between 13.2 °C and 14.1 °C. More than 75% of the annual precipitation falls in the winter and fall. The minimum and maximum mean temperature changes between 7.4–11.0 °C and 16.7–18.6 °C, respectively [35]. The area's land cover comprises mostly forest (62%) and agricultural lands (35%). The remaining area includes pasture/grasslands, artificial surfaces, water bodies, wetlands, and bare lands (Figure 1).

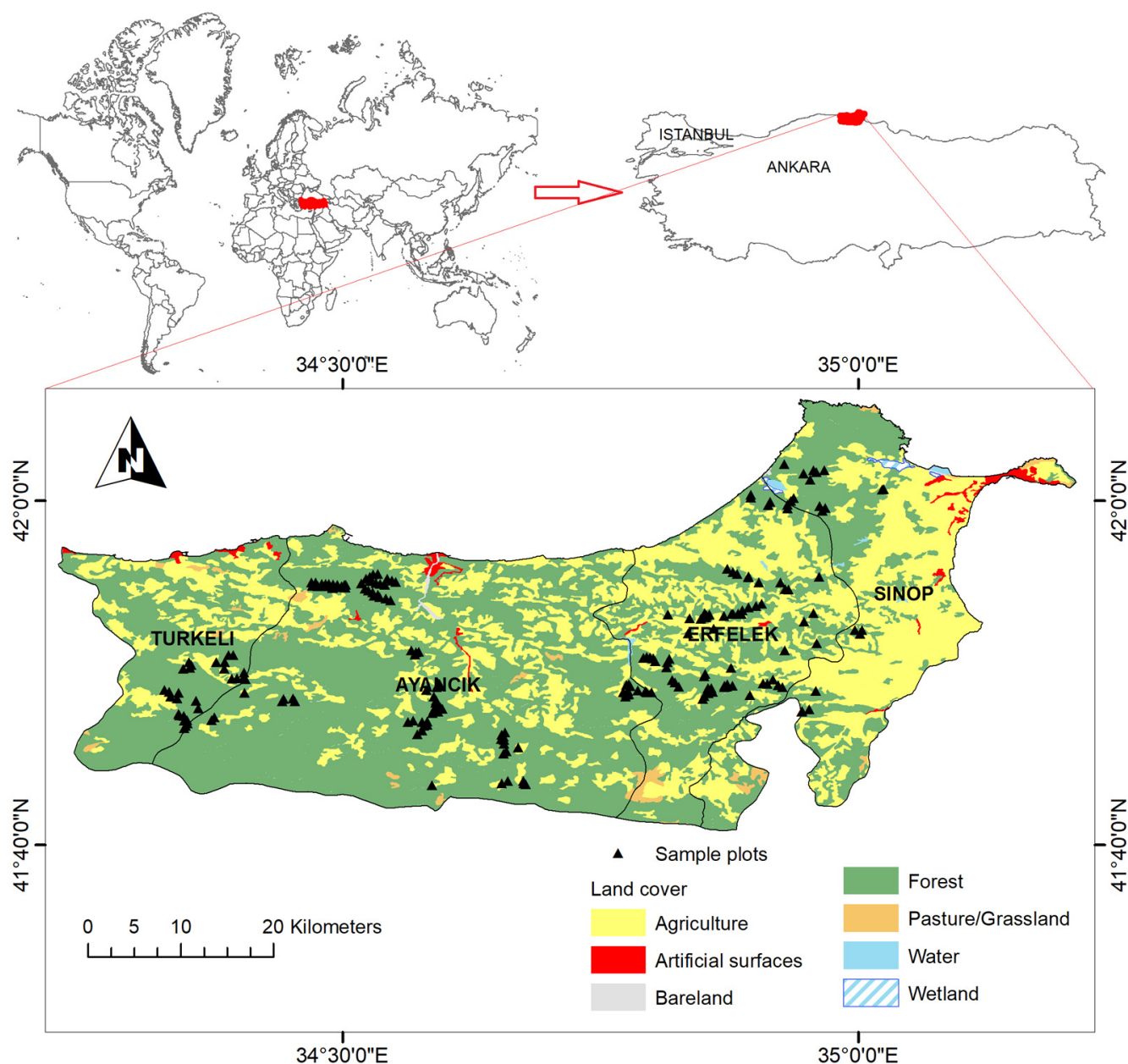


Figure 1. Location of the study area and its land cover classes according to the Cover Corine Land [36].

The vegetation in Sinop is mainly composed of two types: humid forests and pseudo maquis. While the former type includes oriental beech (*Fagus orientalis*), oak (*Quercus* sp.), black pine (*Pinus nigra*), Calabrian pine (*Pinus brutia*), fir (*Abies nordmanniana*), and Scotch pine (*Pinus sylvestris*), the latter includes laurel (*Laurus nobilis*), Irish strawberry (*Arbutus unedo*), saunders (*Arbutus andrachne*), heather (*Erica arborea*), phillyrea (*Phillyrea latifolia*),

bushy juniper (*Juniperus oxycedrus*), rockrose (*Cistus* sp.), and terebinth (*Pistacia* sp.), along with other fruit trees [37].

2.2. Data Collection and Analyses

2.2.1. Field Data Collection

The study was carried out during the summer seasons of 2008, 2009, and 2011 in the oriental beech stands of the regional forestry directorate. To that end, 222 circular sample plots (0.04 ha) were distributed to the entire area in GIS using a stratified random sampling design [38]. We ensured the sample plots were fully stocked and showed no insect or disease trace.

Some environmental variables regarding topography, climate, and soil were used to predict/model the SDH, computed by taking the average height of four dominant trees. The average age of the stands was calculated by counting four dominant trees' rings on the cores at breast height (1.3 m) and then adding ten years to each for seedling age [1,39].

The longitude (LONG), latitude (LAT), aspect (ASP), and elevation (ELEV) data were recorded by a handheld GPS, and the ground slope (SLP) was measured using an inclinometer on each plot. The slope position (SPOS) was noted according to the approach described in Schoeneberger's study [40].

A soil pit was dug up to the bedrock and described according to Cepel's method [41], and disturbed soil samples were taken from the topsoil (at 0–20 cm soil depth) in each plot. Some physical (sand, silt, and clay content and available water capacity) and chemical (pH, organic carbon, electrical conductivity, and lime) properties were also determined on each sample in addition to measuring the soil depth.

In the next step, the soil samples were transferred to the lab. The soil texture and available water capacity (AWC) were determined following the methods of Bouyoucos [42] and pressure desorption [43]. The soils' pH and EC, organic carbon (OC), and lime content were determined following the glass electrode, Scheibler [43], and Walkley–Black wet digestion methods, respectively [44].

2.2.2. Spatial Data Extraction

We used independent variables extracted from the maps shown in Figures 2 and 3. These maps were generated from various data sources and web platforms, like the DEM and GEE. The LONG, LAT, and ELEV datasets were extracted from the DEM using ArcMap conversion tools (i.e., feature to raster) and spatial analyst tools (i.e., extract values to points). The slope (SLP) and aspect (ASP) values were obtained from the surfaces created using the DEM through the ArcMap spatial analyst tool. Then, the aspect values were transformed to the radiation index (TRASP), ranging from 0.0 on the NNE slopes to 1.0 on the SSW slopes, which was calculated using Equation (1) [45].

$$\text{TRASP} = [1 - \cos((\pi/180)(\text{ASP} - 30))]/2 \quad (1)$$

Additionally, the distance to the sea (DTS) was created using spatial analyst tools (i.e., distance) [46]. The coastline vector dataset was obtained from Kelso and Patterson [47]. The other variable to be correlated to the SDH was the normalized difference vegetation index (NDVI) obtained from NASA using the Google Earth Engine platform (Didan, 2015). The NDVI, calculated by Equation (2), serves as a measure of the quantity, health, and spread of green plants within a region, achieved by assessing the spectral reflectance disparity between the red (Red) and near-infrared (NIR) bands of an image [48]:

$$\text{NDVI} = (\text{NIR} - \text{Red})/(\text{NIR} + \text{Red}) \quad (2)$$

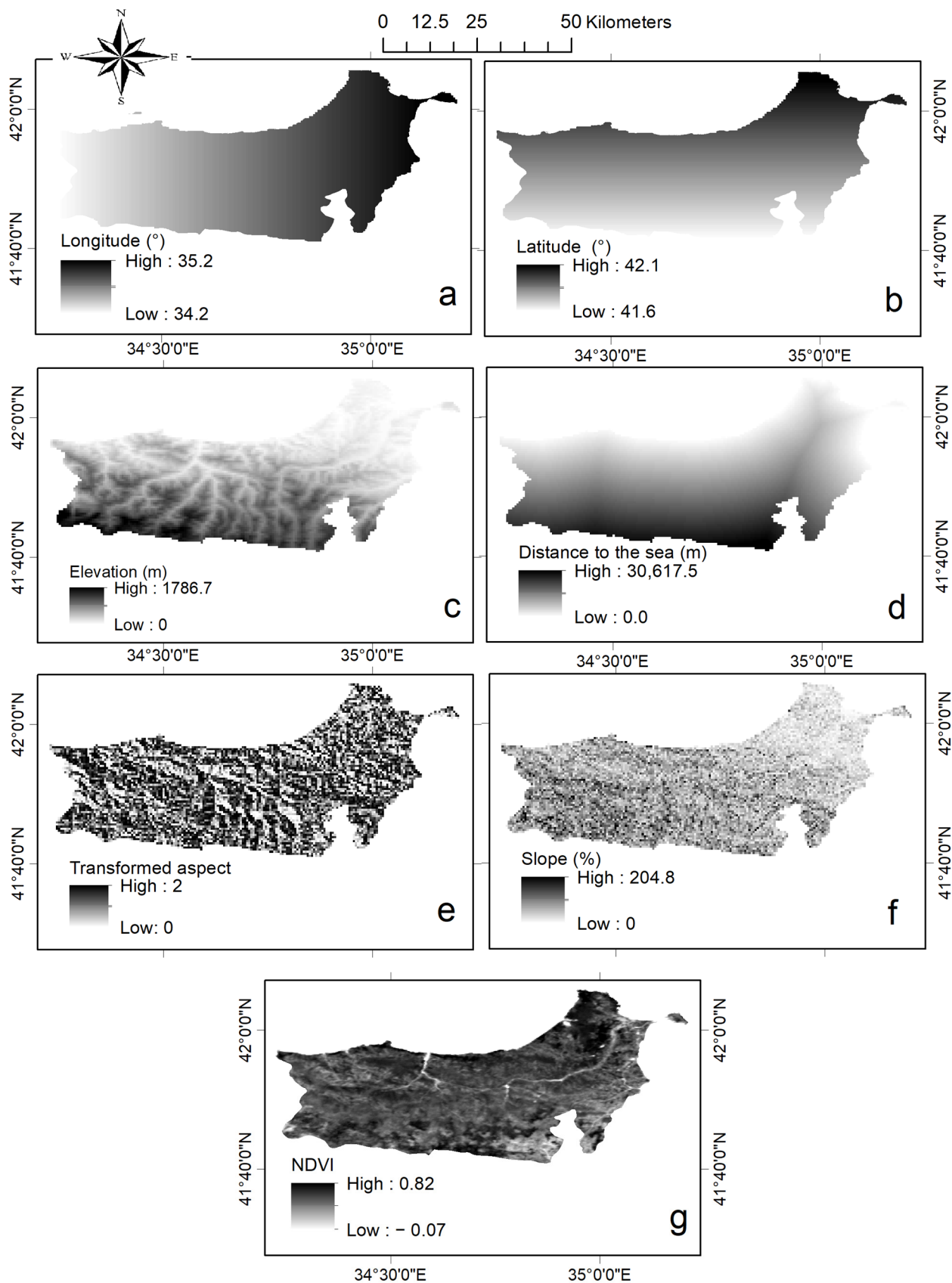


Figure 2. The sources of topographic variables used to model dominant height ((a): LONG, (b): LAT, (c): ELEV, (d): DTS, (e): TRASP, (f): SLP, (g): NDVI).

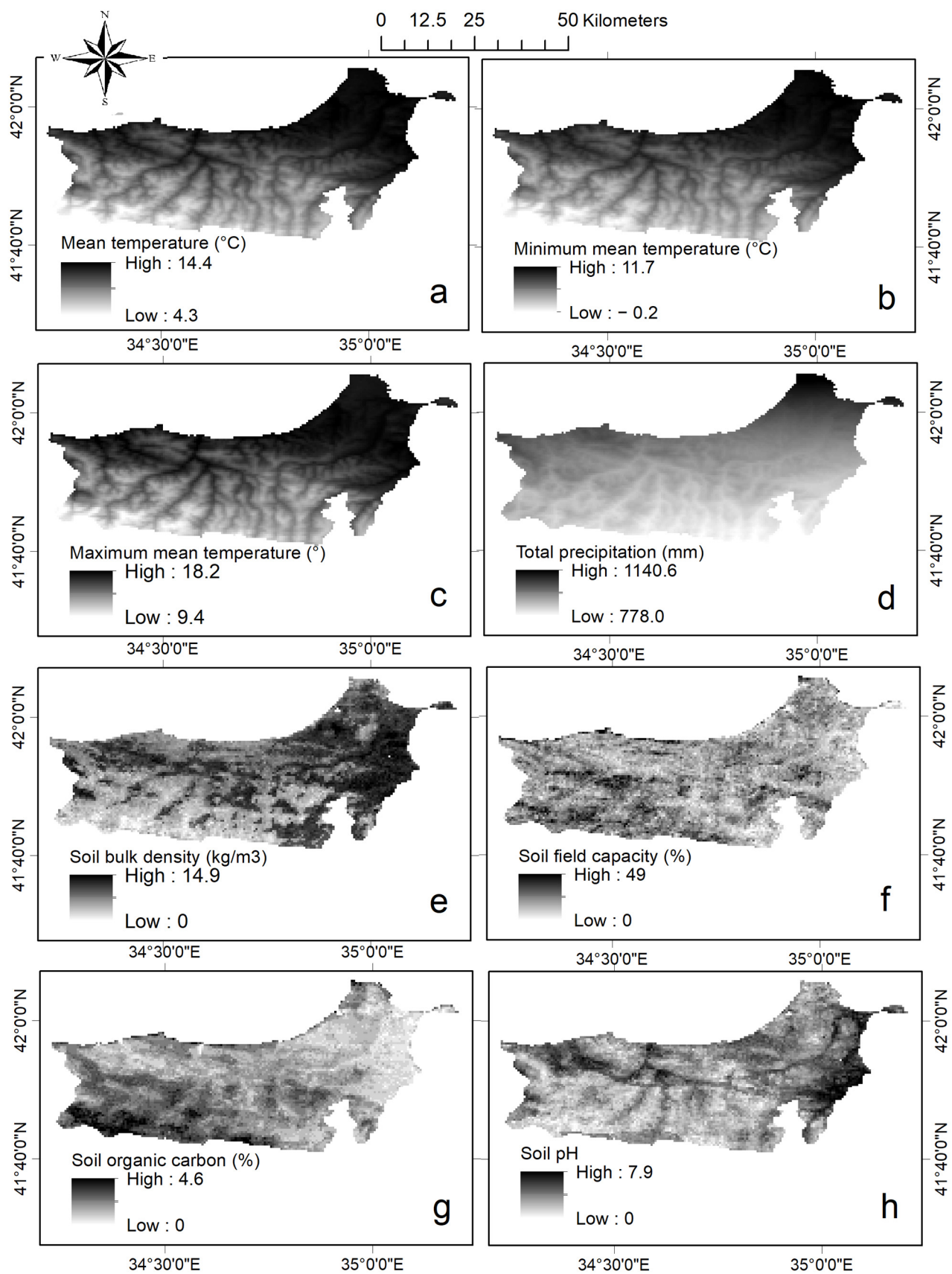


Figure 3. The sources of independent variables used to model dominant height ((a): MAT, (b): MAMINT, (c): MAMAXT, (d): MATP, (e): BD, (f): FC, (g): OC, (h): pH).

The climate variables such as the mean annual temperature (MAT), mean annual minimum temperature (MAMINT), mean annual maximum temperature (MAMAXT), and total precipitation (MATP) were extracted from the spatial climate surfaces developed by Yener [49] at a spatial resolution of $0.005^\circ \times 0.005^\circ$ (approximately 600 m). The soil variables, such as the bulk density (BD), OC, field capacity (FC), and pH, were extracted from the maps provided by Hengl and Wheeler [26] and Hengl [27,28].

2.2.3. Analysis and Mapping

First, Pearson's correlation analysis and partial dependence plots (PDP) were used to analyze the linear and nonlinear relations between the SDH and the other variables. The smoothed PDPs were created for each explanatory variable using the *pdp* package in the R programming language [50]. The PDPs demonstrated whether each predictor affected the response variable while preserving the average of the remaining predictors [8,14]. After determining the correlations between the variables, MLR and RT analyses were performed to model the SDH using the site variables. While the linear and nonlinear relations were determined using R [51], DTREG was used in the modeling [52].

After the RT and MLR models were developed, potential dominant height maps regarding oriental beech stands were generated using Map Algebra in the spatial analyst tools in ArcMap [46]. In this process, the model equations were entered into the software, and the topographic, climatic, and edaphic surfaces in the raster format were introduced to the program as the independent variables (to be used in equations) and then the tool was run [53,54]. While the resolution of the predicted productivity maps was 0.005, equaling 600 m, the used surfaces' resolution was 30 m for the topographic, 250 m for the edaphic, and 600 m for the climatic attributes.

3. Results and Discussion

This section presents three subheadings: field-based data, relationships between the stand dominant height (SDH) and spatial data, and predicting and mapping SDH.

3.1. Field-Based Data

The field data comprised the stand dominant height, stand age, and various soil properties, including the soil depth, texture, available water capacity, pH, electrical conductivity, organic matter, and lime (Table 1). While the oriental beech SDH ranged between 14.6 m and 33.4 m with an average of 22.8 m, the stand ages ranged between 29 and 148 with an average of 73 years. The soil depths across the sample plots changed between 40 and 145 cm, averaging 105.2 cm. Oriental beech is well grown moderate and deep soils [55]. The average soil depth in oriental beech stands ranged from 70 cm to 95.2 cm in other studies [56–59].

The soil texture in the sampled plots was mainly composed of loamy clay (42.0%), heavy clay (14.3%), sandy clay loam (13.4%), sandy loam (11.8%), and others (18.5%) (Figure 4a).

Changing topography, climate, parent material, and living organisms' impact shape the soil texture over time. The soil texture of oriental beech forests varies from heavy clay [60] to loam and sandy loam [61].

The pH ranged between 3.8 and 7.4, with an average of 5.3 (Table 1, Figure 4b). Strongly acid soils dominate the study area with an area share of 45% (Figure 4b). The soil pH range in our study is consistent with those reported in other studies [62–65]. The EC was between 0.1 mS/cm and 6.48 mS/cm, with an average of 0.9 mS/cm. The salinity classes in the study area were formed as non-saline (91%), slightly saline (8%), and moderately saline (1%) (Figure 4c). The soil salinity of beech stands is generally low and characterized as non-saline in most studies [57,60,66]. The soils' organic matter and lime content were 2–10.5% and 0–17.4%, with an average of 3.4% and 1.9%, respectively (Table 1, Figure 4d). The soil organic matter content classes were characterized as high (39%), moderate (31%), very high (20%), and others (10%) (Figure 4d). Topographic and climatic factors affected

the soil OC, along with the soil texture, and the stand characteristics. Therefore, the average OC content of beech stands varied from 1.9–3.0% [61,64] to 3.6–3.9% [55,60,67]. The AWC ranged between 1.9% and 23.3%, with an average of 12.3% (Table 1).

Table 1. Some descriptive statistics regarding observed and digitally extracted variables.

	Variables	Abbr.	Minimum	Maximum	Mean	SE	SD
Digitally extracted variables	Longitude (°)	LONG	34.3	35.0	34.7	<0.1	0.2
	Latitude (°)	LAT	41.7	42.0	41.9	<0.1	0.1
	Elevation (m)	ELEV	12.0	1352.0	630.9	21.8	324.6
	Distance to the sea (m)	DTS	692.5	24,935.8	12,279.0	385.3	5741.2
	Transformed aspect	TRASP	0.0	2.0	1.1	<0.1	0.7
	Slope (%)	SLP	5.0	84.4	31.8	1.1	16.8
	Vegetation index	NDVI	0.6	0.7	0.7	<0.1	<0.1
	Mean temperature (°)	MAT	6.8	14.1	10.6	0.1	1.8
	Minimum mean temperature (°)	MINMT	2.5	11.3	7.0	0.1	2.2
	Maximum mean temperature (°)	MAXMT	11.5	17.5	14.8	0.1	1.5
	Total precipitation (mm)	TP	806.4	1072.9	925.4	3.6	54.3
	Soil bulk density (kg/m ³)	BD	10.0	13.8	11.5	0.1	0.9
	Soil field capacity (%)	FC	30.0	40.0	33.5	0.1	2.0
	Soil organic carbon (%)	OC	0.8	2.8	1.6	<0.1	0.4
	Soil pH	pH	5.3	6.7	6.0	<0.1	0.3
Observed variables	Stand dominant height (m)	SDH	14.6	33.4	22.8	0.2	3.7
	Stand age (year)	SA	29.0	148.0	73.3	1.4	21.2
	Soil depth (cm)	SDEPTH	40.0	145.0	105.2	1.2	18.2
	Sand content (%)	SAND	21.0	90.0	51.3	0.9	14.3
	Silt content (%)	SILT	3.0	39.0	18.5	0.4	6.0
	Clay content (%)	CLAY	5.0	60.0	30.2	0.8	12.0
	Available water capacity (%)	AWC	1.9	23.3	12.3	0.2	3.3
	Soil pH	pH	3.8	7.4	5.3	0.1	0.8
	Soil electrical conductivity (mS/cm)	ECe	0.1	6.48	0.9	0.1	0.9
	Soil organic carbon (%)	OC	0.2	10.5	3.4	0.1	2.0
	Soil lime content (%)	LIME	0.0	17.4	1.9	0.1	2.1

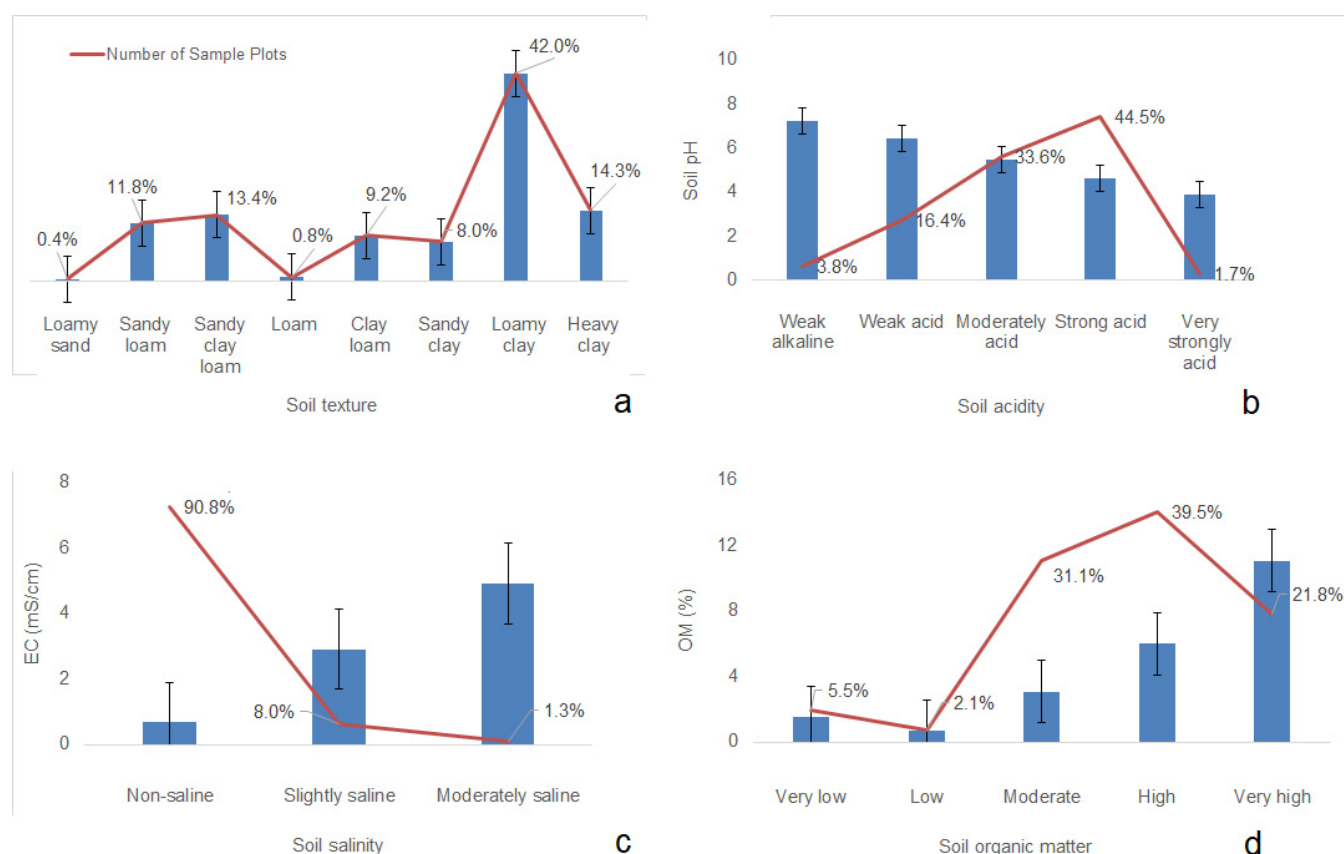


Figure 4. Distribution of sample plots to soil properties classes ((a): texture, (b): acidity, (c): salinity, (d): organic matter).

3.2. Relationships between the Stand Dominant Height (SDH) and Spatial Data

This study used digitally extracted data as the explanatory variables to model and map the oriental beech stands' dominant height. While the Pearson correlation determined the relationships between the SDH and the explanatory variables (Figure 5), the partial dependence plots visualized these relations (Figure 6). The variables included were topographic (i.e., LONG, LAT, ELEV, DTS, TRASP, SLP, and NDVI), climatic (i.e., MAT, MAMINT, MAMAXT, and MATP), and edaphic (i.e., BD, FC, OC, and pH).

Assessing the spatial data retrieved from various resources (Table 1), we saw that our sample plots were located between 34.3°–35.0° N longitudes and 41.7°–42.0° E latitudes. The ELEV ranged from 12 m near sea level to 1352 m with an average of 630.9 m. The average DTS was 12,279 m in the area and reached up to 24,935 m. The slope of the sample plots changed between 5 and 84.4%, with an average of 31.8% corresponding to steep slopes. The NDVI also assessed as part of the topographic variables averaged 0.66, ranging between 0.59 and 0.75, which is relatively high.

Of these variables, the ELEV was positively correlated ($r = 0.36$), and the LAT ($r = -0.25$) and NDVI ($r = -0.24$) were negatively correlated with the SDH. No significant relationships existed with the other topographic variables ($p > 0.05$) (Figure 5). The DTS, LAT, and ELEV are essential factors in determining the regional climate parameters, such as temperature, precipitation, and radiation, affecting forest productivity [19,68]. While the latitude impacts those parameters' distribution, increasing the ELEV shortens the growing period due to the decreasing temperature and increases the relative humidity [69]. The negative effect of reducing the ELEV on the SDH could be attributed to the optimum altitudinal zone for the oriental beech stands in Sinop, which is between 600 m and 1200 m with an average of 1000 m [70].

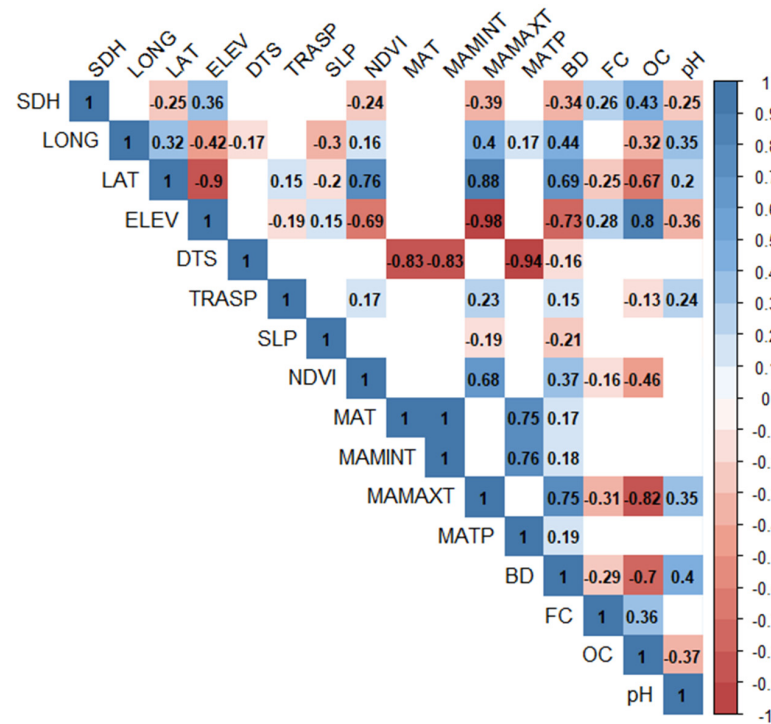


Figure 5. Correlation matrix showing the linear relationships between explanatory variables and SDH. The blank boxes indicate the nonsignificant relationships between variables, and the numbers in the boxes show the correlation coefficients.

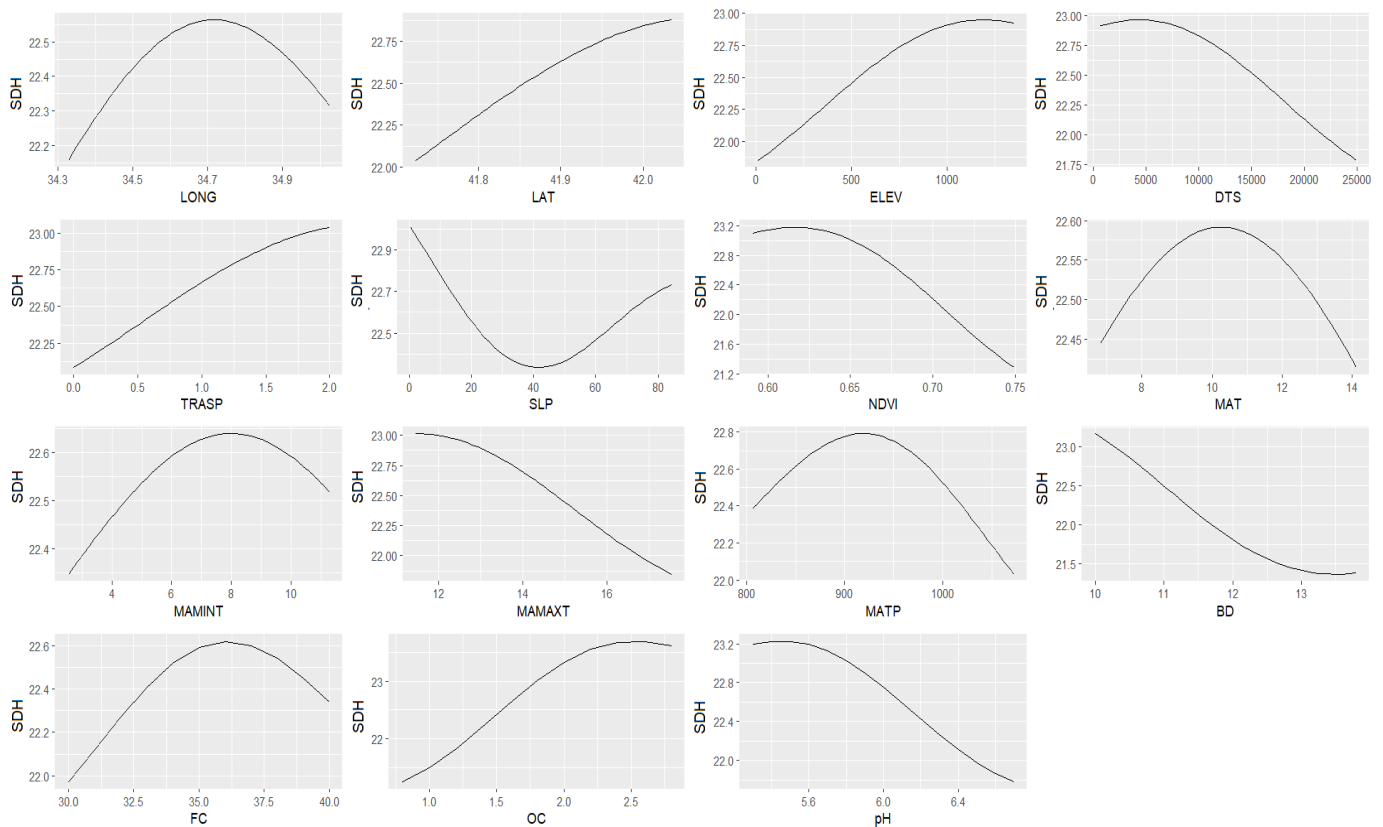


Figure 6. Partial dependence plots showing the nonlinear relations between dependent and independent variables.

Therefore, increasing the elevation improved the SDH. The altitudinal zone could also explain the negative correlation between the LAT and SDH. This is because increasing the LAT means decreasing the elevation ($r = -0.9$) (Figure 5). The partial dependency plots, showing nonlinear relations, indicated that the SDH increased with the ELEV increasing up to 1000 m and then decreased (Figure 6), which could be proof of the optimum altitudinal zone being below 1000 m for oriental beech stands. Similar results on the effect of the ELEV on stand productivity were found in other studies [7,12,14,58,71]. For example, Alavi et al. [7] also attributed increased productivity in oriental beech stands of Hyrcania, Iran, to increasing the ELEV to the optimum altitudinal zone, above 1500 m. Güner et al. [72] linked this positive effect of the ELEV on Anatolian black pine productivity to improved precipitation at higher altitudes. However, other authors [4,14,15] reported conflicting findings due to deteriorated ecological conditions with increasing ELEV, such as shortening the growing period, decreasing fine-textured soil, and reducing decomposition due to the condensing temperature. The reducing effect of LAT on stand productivity was also reported in some studies [14,73]. Klinka et al. [73] reported a decrease of 2.9 m in the Norway spruce SI and 2.5 m in the Douglas fir SI with a 1° increase in latitude and 100 m in elevation.

Another topographic variable correlated with the SDH was the NDVI, whose relatively higher value above 0.6 in the study area indicates dense vegetation cover. Its weak negative correlations with the SDH could also be linked to somewhat higher altitudes ($r = -0.69$ between the NDVI and ELEV, Figure 5), regarded as the oriental beech's growing optimum. It is also associated with decreasing precipitation in beech sites due to going southward, negatively affecting the NDVI ($r = 0.76$ between the NDVI and LAT, Figures 3d and 5) [74,75]. On the contrary, some other researchers found positive correlations between the NDVI and site productivity [21,22,76–78].

The climatic variables used in this study were extracted from the climate surfaces developed by Yener [49]. According to this dataset, the study area's climate is characterized by an average of 10.6°C mean, 7.0°C mean minimum, and 14.8°C mean maximum temperatures with minimum–maximum values of 6.8 – 14.1°C , 2.5 – 11.3°C , and 11.5 – 17.5°C , respectively (Table 1, Figure 3a–c). The precipitation in the study area ranged from 806.4 mm to 1072.9 mm and averaged 925.4 mm (Table 1, Figure 3d). Climate, one of the main ecological factors affecting terrestrial ecosystems at global and local scales, is the driving force for the biogeochemical cycle in nature [17,69]. Variable climatic conditions also affect biomass and soil litter decomposition and carbon accumulation [79]. Therefore, the MAT, MAMINT, MAMAXT, and MATP were used in this study; however, the MAMAXT was the only climatic factor significantly correlated with the SDH ($r = -0.39$) (Figure 5).

Our finding is similar to those reported in other studies [12,13,80,81]. The negative effect of the MAMAXT on the SDH may be attributed to enhanced summer drought [80]. Seltmann et al. [13] reported improved Norway spruce growth because of the low temperature and high AWC. However, the temperature in most studies [14,15,82,83] positively affected tree growth, attributed to prolonged growing periods, enhancing microbial activities and improving decomposition and soil attributes. Although no significant effect of precipitation on the SDH was observed in this study, some other studies [13,72,80,81,83] reported that it somehow affects stand productivity. Likewise, we detected no significant climatic variables, except for the MAMAXT. The partial dependence plots (Figure 6) showed that the SDH increased with an increasing MAT and MAMINT and MATP up to about 10°C , 8°C , and 950 mm, respectively, and then suddenly decreased.

The digitally extracted BD, FC, OC, and pH averaged 11.5 kg/m^3 , 33.5%, 1.6%, and 6.0, respectively, and ranged between 10.0 and 13.8 kg/m^3 , 30 and 40%, 0.8 and 2.8%, and 5.3 and 6.7, respectively (Table 1, Figure 3e–h). All the digitally extracted edaphic variables significantly affected the SDH: while the BD ($r = -0.34$) and pH (-0.25) were negatively associated with the SDH, the FC ($r = 0.26$) and OC ($r = 0.43$) positively affected it (Figure 5).

The positive effect of the FC or FC-based AWC on stand productivity was reported in other studies [8,13,58,59]. Soil moisture or water is one of the most important ecological

factors affecting plant growth, especially in influencing soil temperature, aeration, microbial activity, and nutrient availability and diminishing the toxic material concentrations, besides directly providing water to the plants [84]. The situation in which the OC was positively correlated with the SDH could be attributed to the provided functions of organic matter on soil quality through an increased cation exchange and available water capacity, improving soil aggregates, aeration, and porosity and providing nutrients [85,86]. Similar findings were reported by Aertsen et al. [87] and Subedi and Fox [88]. Results, in contrast to ours, were also found by some other researchers [4,58], attributing their outcomes to decreased pH with increasing organic matter. Unlike the FC and OC, the BD and pH negatively affected productivity in the present study. An indicator of soil acidity, pH mainly affects some processes, such as nutrient availability, nitrification, microbial activity, and heavy metal toxicity [89]. Most of the studies [71,87,88] reported a positive effect of pH on productivity, attributing it to improving soil conditions, such as nutrient availability and microbial activity. However, some other researchers [7,64] reported contrasting results in disagreement with our study. Our results showed that pH is one of the limiting factors for the dominant height growth of oriental beech. An increasing pH negatively affects some elements' availability in the soil solution, such as phosphorus, iron, zinc, and manganese [7]. The BD is calculated by summing the soil pores and solids to the soil volume; its unit is gr/cm^3 . A low BD indicates a loose and highly porous structure due to the high organic matter in soils [86], consistent with our finding in Figure 5, showing $r = -0.7$ between the BD and OC. Increases in BD generally result in adverse effects on tree development through the negatively affected mentioned soil properties [90]. As a matter of fact, Irmak [91] and Cepel [41] stated that the effect of soil properties on stand development becomes more evident when the climate is not very variable, and the species moves away from the optimum conditions.

3.3. Predicting and Mapping SDH

The presented study aimed to predict the SDH from spatial data, including topographic, climatic, and edaphic variables, using MLR and RT analyses and then generating potential SDH maps using those models. We randomly selected 75% of the sample plots as the training datasets in this context, withholding the remaining 25% as validation. The model results showed that MLR accounted for 26% and 21% of the variation in the SDH, with an RMSE of 3.16 m and 3.27 m for training and validation, respectively. RT outperformed MLR, explaining 57% and 25% of the variation, with an RMSE of 2.37 m and 3.33 m for training and validation, respectively (Figure 7). The RT model included at least one variable from any group, such as topographic, climatic, and edaphic; however, MLR included only climatic and topographic variables.

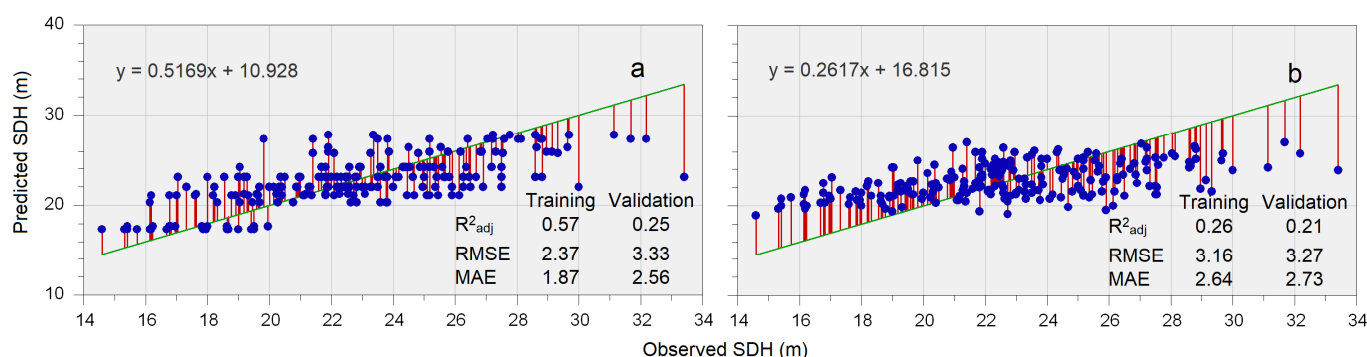


Figure 7. Correlations and error metrics between observed and predicted SDH ((a): RT model, (b): MLR model).

The most critical variable in the models was MAMAXT for MLR and BD for RT, with an importance of 62.3% and 37.5%. The most critical factor group affecting the SDH was the

climate, with an importance rate of 62.3%, and the soil, with an importance rate of 61.2% for the MLR and RT models (Figure 8).

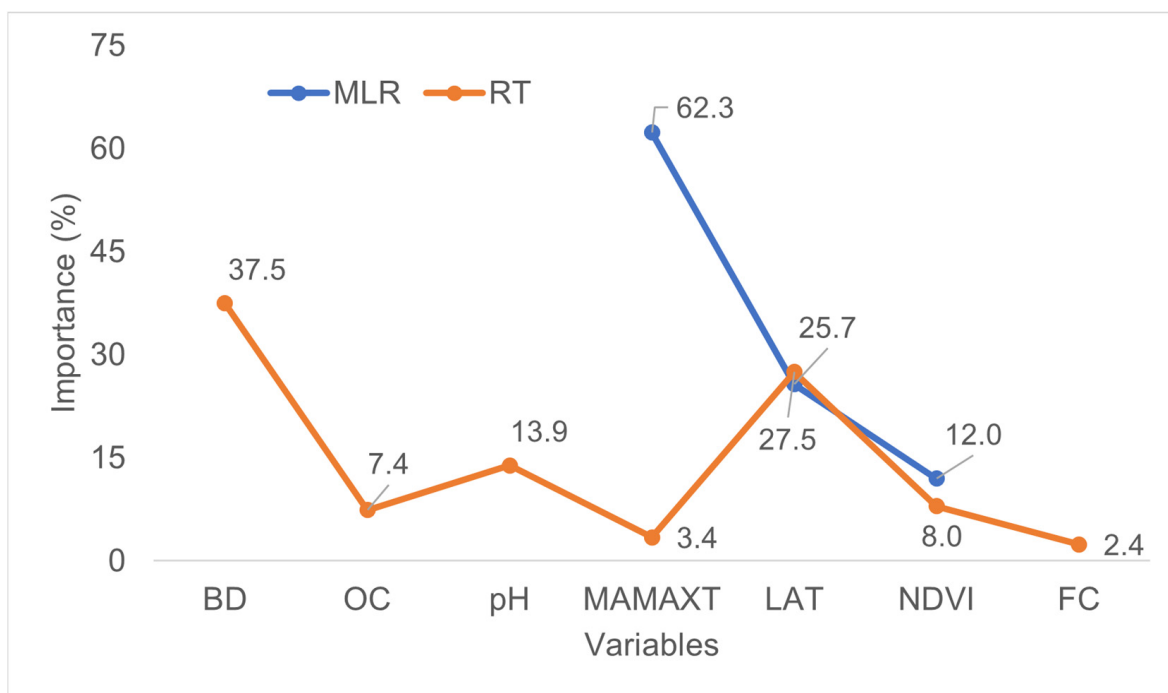


Figure 8. Variable importance in models.

Many studies [4,12,15,16,71,72,82,92] have used MLR and RT for estimating forest productivity. Our model results are consistent with those reported in other studies [4,5,12,15,72,92–94]. The most satisfied results in these outperformed models were reached as an adjusted R^2 of 0.85 and RMSE of 1.17 m for the training dataset and an R^2 of 0.54 and RMSE of 1.91 m for validation by Alavi et al. [7] in the Hyrcanian oriental beech forests of Iran using edaphic and physiographic variables. Mohammadi et al. [5] also predicted oriental beech productivity, e.g., stand volume using MLR and RT techniques, and RT outperformed with an R^2 of 0.67 (percentage RMSE = 30%). Some other statistical approaches have also been implemented to model forest productivity, such as the complementary methodological approach [95], random forest analysis [14,96,97], Chapman–Richards model [83,98], and linear mixed effects models [99].

In an RT analysis, a particular site productivity indicator, such as the dominant height and site index, is classified by considering the predictors (independent or explanatory variables). The precise value of the predictor optimally splits the data at any branch of the tree [100].

The RT model in this study included seven independent variables: edaphic (BD, pH, OC, and FC), topographic (LAT and NDVI), and climatic (MAMAXT). The soil BD, with a variable importance of 37.5%, followed by the LAT (18.5%) and pH (13.9%) (Figures 8 and 9), is the first and primary variable controlling the SDH. At this point, a BD below or equal to 1.1 gr/cm^3 resulted in an SDH of 24.6 m. However, a BD above that value corresponded to an SDH of 21.4 m., which was 13% lower than the previous one, suggesting that a decreased BD (below 1.1 gr/cm^3) improves the SDH. The second important node was an LAT above 41.8° interacting with a BD equal to or below 1.1 gr/cm^3 , an OC equal to or below 2.1%, and an FC above 34.5%, resulting in a 27.8 m SDH, the highest value in this model followed by the BD (equal to or below 1.1 gr/cm^3) and OC (above 2.1%) interactions corresponding to the 27.2 m SDH.

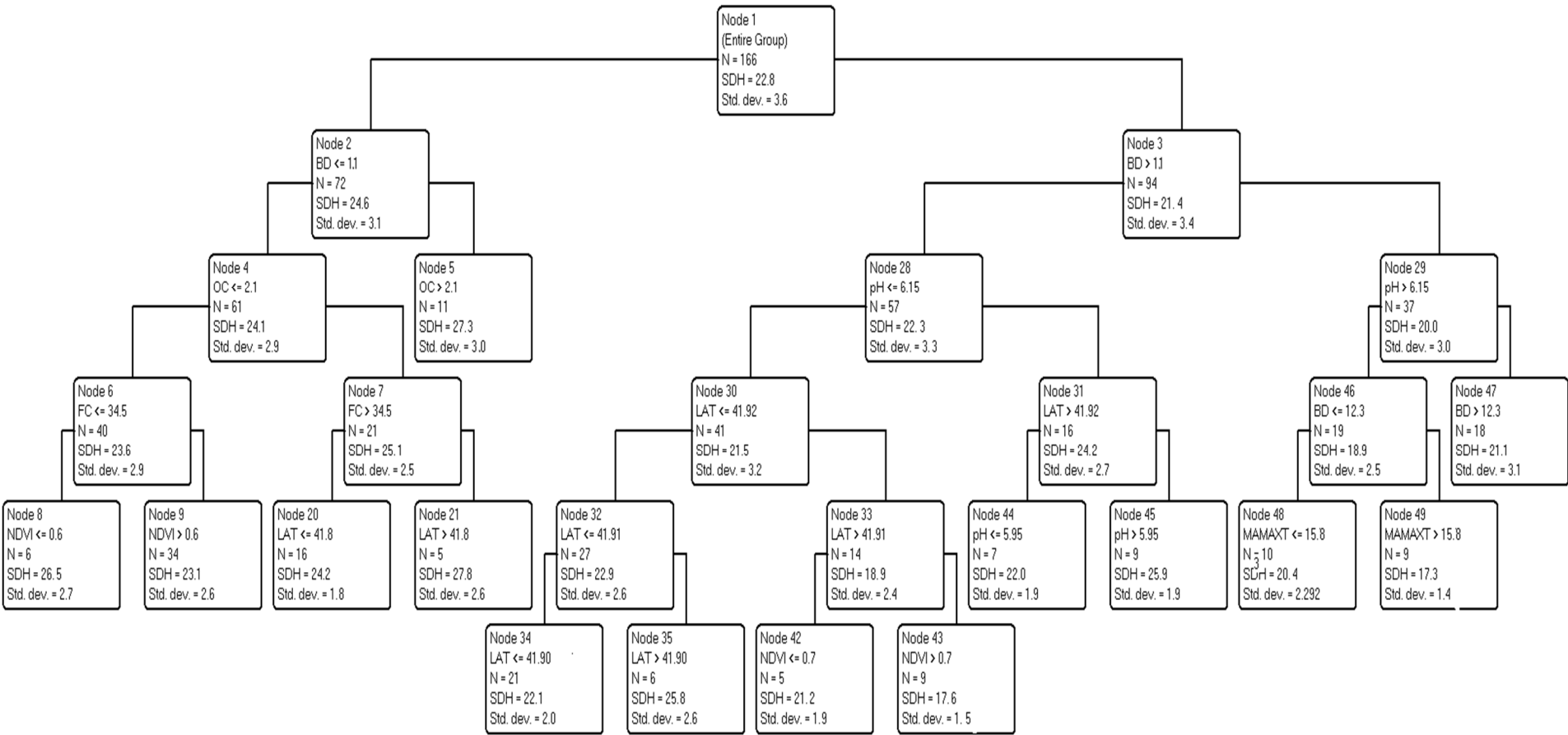


Figure 9. Regression tree model to predict SDH of oriental beech stands.

This RT model suggests that it is vital to establish oriental beech stands where the BD is below 1.1 gr/cm^3 and the OC is above 2.1%, or the BD is equal to or below 1.1 gr/cm^3 , the OC is equal to or below 2.1%, the FC is above 34.5%, and the LAT is above 41.8° . It also suggests that the sites with a relatively higher BD ($>1.1 \text{ gr/cm}^3$) with a pH equal to or below 6.15 and an LAT below 41.9° are more productive than sites with more than 6.15 pH.

Afif-Khouri et al. [71] and Menendez-Miguel et al. [82] also used RT to predict the stand productivity in NW Spain chestnut coppice stands. While extractable Mg and annual temperature were the only determinants in the former study, the latter research determined the clay content of soils and the spring and summer precipitation as nodes in the RT. On the other hand, the MLR model comprises the MAMAXT, LAT, and NDVI, which were also included in the RT model.

We also mapped the potential productivity of the oriental beech forest in the study area. The resolution of the maps shown in Figure 10 is 0.005° (600 m/pix). According to the maps, the stand dominant height was between 22.4 and 43.3 m for MLR and 17.3 and 27.8 m for the RT model. However, with some differences in the model maps, the productivity increases toward the area's inner part, especially to the southwest (Figure 10). This improvement could be explained by enhanced ecological conditions in this part, such as an elevated OC (Figure 3g) and FC (Figure 3f), a decreased BD (Figure 3e), and reaching the optimum altitudinal zone in terms of air temperature (Figure 2c), suggesting that coastal areas are unsuitable for oriental beech in this region.

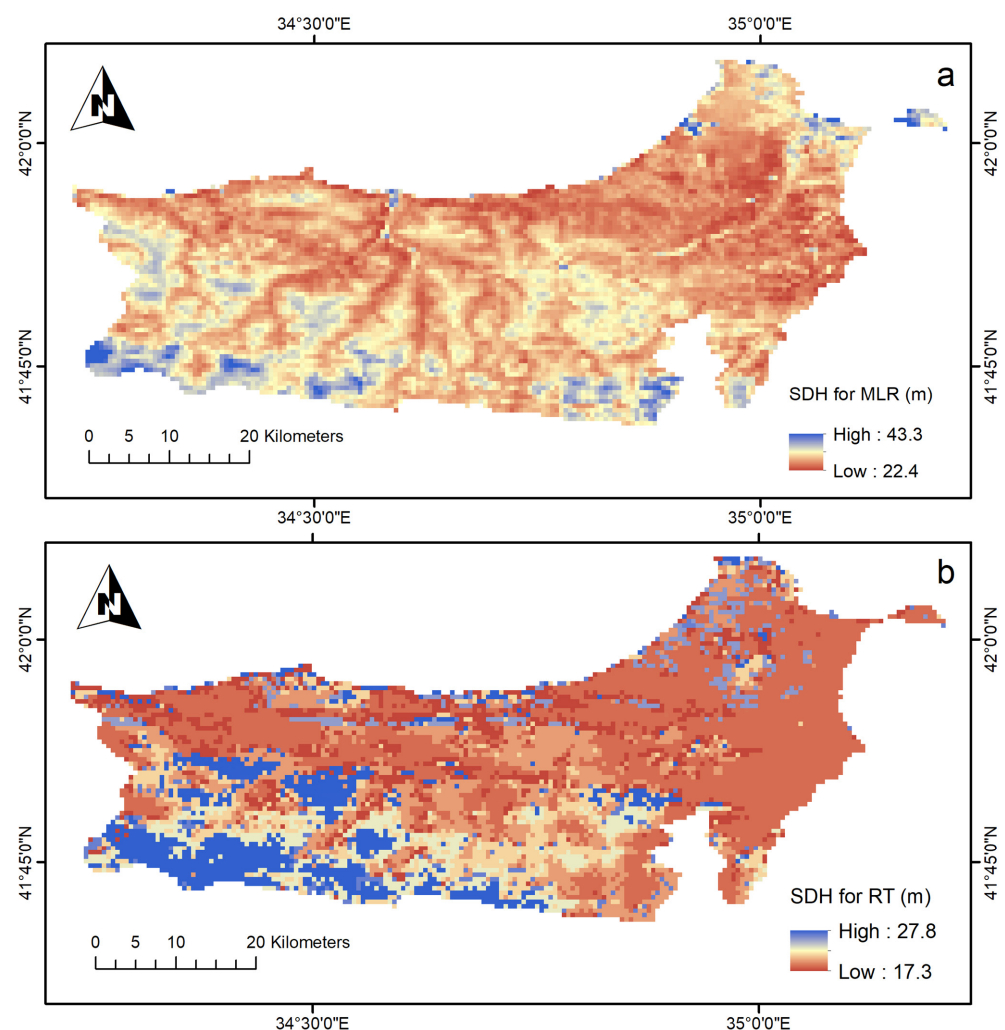


Figure 10. Spatial distribution of oriental beech SDH across the study area. Map generated by MLR (a) and RT (b) models.

The other point is decreased productivity in the region's eastern part, which can be attributed to the increased temperatures and decreased organic matter. Other researchers [6,23,101–103] have also mapped forest productivity at variable spatial resolutions, ranging from 5 m to 1000 m. They used soil, climate, and terrain attributes based on different statistical techniques, like RF, RT, Chapman–Richards, and MLR. While Swenson et al. [103] predicted and mapped the SI for Douglas fir stands with an R^2 of 0.55 and RMSE of 6.1 m in the USA, Jiang et al. [101] found those values to be an R^2 of 0.64 and RMSE of 4.6 m for softwood and an R^2 of 0.36 and RMSE of 4.2 m for hardwood species also in the USA.

4. Conclusions

Because there is insufficient knowledge of the spatial variation of species-specific site productivity, generating dominant height maps is crucial for forest management practices, such as reforestation and plantation. The maps generated in this study could help forest planners and land managers visualize the most productive oriental beech sites rapidly. Our approach can also be used in locations with different vegetation types if site-specific spatial data are available.

Based on the results, it is concluded that the RT model outperformed the MLR model with more accurate estimates and maps. The RT model emphasizes that edaphic factors should be given more importance than others, particularly in oriental beech afforestation and reforestation works. Using freely available spatial datasets with more spectral data and the RT technique, researchers can develop new site productivity models and generate wall-to-wall maps of their area of investigation. Thus, site productivity can be assessed in a spatially explicit manner.

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